NON-COHERENT DIGITAL MODULATION CLASSIFICATION USING CONSTELLATION SHAPE

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ABSTRACT
This paper reports on the performance of a newly proposed modulation classification technique in a non-coherent, high noise environment. The algorithm is novel in the sense that modulation type is identified based on the shape of signal's constellation. The recovered constellation, however, is a deformed copy of the original. This deformation is modeled by a discrete non homogenous binomial random field followed by a MAP decision rule. In this paper we evaluate the performance of constellation shape based modulation classification in an AWGN channel and symbol-noncoherent receiver. Results for classifying between V.29 and 16QAM square modulation show near perfect results for Eb/No of as low as 7 dB and peak phase error deviation of $\pi/8$. These results show that a multidimensional shape is a significantly more robust modulation signature than other conventional test statistics.

1. INTRODUCTION
Most signals of interest are characterized by their specific modulation type. Automatic recognition and classification of this information is of considerable interest in applications involving spectrum surveillance and management, interference identification, military threat evaluation, electronic counter measures and many others. Knowledge of the modulation type of a signal may also provide clues to its origin and mission.

Past modulation classification algorithms have followed two distinct approaches; statistical pattern recognition and decision theoretic. More recent papers have generally favored the decision theoretic technique. In this approach, a likelihood function is formed from the observed signal followed by statistical hypothesis testing[2,4,10,13,3]. Such formulations, however, have been narrowly defined for specific modulation types, most frequently MPSK, and are not generally scalable. Also, the optimality of likelihood functional is sometimes compromised for practical reasons[10]. Other approaches such as Mth law non-linearity and filtering reveals bulges in the spectrum at M times the carrier frequency of an MPSK signal. Statistical moments of the signal has been used as sufficient statistics to classify among various MPSK signals[11]. More recently, subspace methods[15], wavelet packets[12], sequential LR tests[4], higher-order correlations[1] and neural networks[9] have been used for modulation classification.

In this work we first review the basis of constellation shape based modulation classification in an AWGN channel. We will then describe the problem this approach will face in a non-synchronous or weakly synchronous environment. Under such conditions, the constellation shape undergoes contortions that distort its shape over and above random noise effects. We then pick two similarly shaped modulation schemes, V.29 and a square 16QAM, and demonstrate the robustness of the classification algorithm under such conditions.

2. FRONT-END PROCESSING
In previous works, the elements of constellation shape-based modulation recognition have been described[6,7]. An on-line overview is available at [8]. Briefly, This approach is based on 4 steps, 1): building of the IQ scatter data after observing $N$ received symbols, 2): recovery of the original signal constellation using a minimum variance clustering algorithm based on the fuzzy c-means, 3): modeling of the reconstructed constellation by a discrete random field and 4): modulation classification based on a $T$ second observation of the signal.

The received signal's complex envelope can be written as

$$\tilde{r}(t, \theta_c) = \sum_{k=1}^{N} R_k e^{j(\theta_k t + \phi_i)} p(t - (k-1)T_s) + R_k e^{j\theta_k}$$  \hspace{1cm} (1)$$

where $N$ is the number of observed symbols, $R_k$ kth symbol amplitude $\theta_k \in \left\{ \frac{2\pi}{M} i, i = 0, ..., M - 1 \right\}$.
, $M$ number of phases, $T_s$ symbol duration, $\theta_c$ carrier phase tracking error and $p(t)$ the baseband pulse. Noise is white with a two-sided spectral density of $N_0/2$. For a parallel constellation recovery, received signal is fed through a bank of $N$ correlators. The output of this filter bank is an $\times 2$ vector with the $k$th row defined by

$$
\tilde{r}_k(\theta_c, \varepsilon) = \tilde{r}_q, k(\theta_c, \varepsilon) + j\tilde{r}_q, k(\theta_c, \varepsilon) = R_c e^{j(\theta_c + \varepsilon)} \int_{(k-1)T_s}^{kT_s} [p(t-(k-1)T_s) + R_c e^{j\theta_c}] dt
$$

$$
k = 1, ..., N
$$

(2)

In the absence of errors in timing phase, $\varepsilon$, and a constant phase tracking error, the scatter diagram will be a rotated version of the original plus additional disturbances by random noise. What we will consider in this paper, however, is the symbol-noncoherent case whereby phase lock error changes for every symbol. Therefore, each modulation state undergoes a phase offset different from other symbols and different from its own previous state. Fig. 1 is the received IQ scatter of a V.29 signal in an AWGN channel using a symbol-non-coherent receiver.

![Figure 1. Eb/No of 0dB, as well as phase lock error completely smears the original modulation states. Original constellation is shown by white circles](image)

3. CONSTELLATION RECOVERY AND A DEFORMATION MODEL

Let $C = \{C_1, C_2, ..., C_K\}$ be $K$ expected constellations. As a binary field, the $j$th constellation consisting of $M_j$ states can be modeled by

$$
C_j(r) = \sum_{i=1}^{M_j} \delta(r-u_{ji}), j = 1, ..., K
$$

$$
\delta(r-u_{ji}) = \begin{cases} 
1 & r = u_{ji} \\
0 & r \neq u_{ji}
\end{cases}
$$

(3)

Define the reconstructed constellation by another set $\hat{C} = \{\hat{C}_1, \hat{C}_2, ..., \hat{C}_K\}$ each related to the original copy by a deformation process. Boldface notation is used to emphasize that the reconstructed constellations are stochastic entities with $\hat{C}_j$ as a single realization of $\hat{C}_j$. We model the reconstructed constellation by a two dimensional discrete random process defined by random placement of delta functions throughout the constellation space.

$$
\hat{C}_j(r) = \sum_{i=1}^{M_j} \delta(r-v_{ji}), j = 1, ..., K
$$

(4)

where $v_{ji}$ is the estimate of the $i$th constellation point $u_{ji}$. Therefore, for any particular position on the constellation plane, $\hat{C}_j(r)$ may take on any value from 0 to $M_j$. This event is possible because, theoretically at least, there may be more than one rebuilt constellation vertex falling inside a resolution element. Another key observation is that $\hat{C}_j(r)$ is a non-homogenous binomial random field, i.e. its statistics depends on position vector $r$. The statistics of $\hat{C}_j$ are computed off-line as a multidimensional pdf defined over the constellation space, or plane, in the 2D case.

4. NONCOHERENT MODULATION RECOGNITION

In a carrier-coherent situation, $\theta_c$, carrier phase angle, is assumed known. As such, it only introduces a fixed, known rotation of the entire constellation. Under a more realistic condition of carrier-noncoherent receiver, $\theta_c$ is random but is assumed constant during the observation interval $T$. This will also cause a fixed constellation rotation but the angle of rotation will change form one reconstruction to another. Under a symbol-noncoherent scheme, $\theta_c$ is random but remains fixed for the duration of a symbol only. It is the latter condition that we will pursue at this point.

The reconstructed constellation $\hat{C}$ under a symbol non-coherent environment results can be written by

$$
\hat{C}(r) = \sum_i \delta(r-(u_i + n)e^{j\theta_i})
$$

(5)

With $\{u_i\}$ denoting the original $i$th modulation state. It is clear that each state vector is undergoing a different and random rotation relative to its original position. In contrast, a carrier-noncoherent demodulation would have resulted in a $\hat{C}$ given by
\[
\hat{C}(r) = \left[ \sum_i \delta(r - (u_i + n)) \right] e^{j\theta}
\]

To demonstrate this phenomenon, we have reconstructed 25 copies of a square 16QAM signal after observing 320 symbols per constellation at an Eb/No of 7 dB and a peak phase lock error of \(\pi/8\). Each reconstruction is in effect a single sample function of the random field describing the 16QAM signal. Notice that in spite of a low SNR and rather large phase sync error, the recovered constellations show a remarkably tight grouping around the 16 original positions. This property is the key to the robustness of a constellation shape-based matching.

![Image of reconstructed constellations]

**Figure 2.** 25 superimposed reconstructions of a square 16QAM signal with Eb/No=7 dB and peak phase sync error of \(\pi/8\).

Selecting the most likely modulation type based on a single observation of the reconstructed constellation is performed under the MAP rule below

\[
P(C_j | \hat{C}) = \frac{p(\hat{C}|C_j) p(C_j)}{p(\hat{C})}
\]

(7)

\(p(\hat{C}|C_j)\) is evaluated for the joint event

\[
\hat{C} = \{ \hat{C}(r_1) = 1, \hat{C}(r_2) = 1, \ldots, \hat{C}(r_M) = 1 \}
\]

where \(r = \{r_1, r_2, \ldots, r_M\}\) are the recovered modulation states. Exploiting the independence property,

\[
p(\hat{C}|C_j) = \prod_{i=1}^M p(\hat{C}(r_i)|C_j)
\]

(8)

then

\[
C_j = \arg \min \left\{ \sum_{j=1}^M \log \left[ p(\hat{C}(r_j)|C_j) \right] \right\} \quad j \in \{1, \ldots, M\}
\]

(9)

What is being maximized here is the summation of \(M\) amplitudes. These amplitudes come from \(M\) positions on the conditional density surfaces of candidate constellations. For each candidate modulation type, these probabilities are pre computed using (8) and a decision is arrived at in (9).

5. EXPERIMENTAL RESULTS

We have implemented the algorithm on two alternative modulations, 1): V.29 and 2): square 16QAM. Both constellation consist of 16 \{amplitude, phase\} combinations that are closely spaced.

The first step in the process is an energy normalization phase. Signals arrive with vastly different power levels. Moreover, the reconstructed constellation must match the constellation model library in scale. Following this step, we must then characterize the statistics of the random field associated with each modulation scheme. This is done for both schemes using 25 iterations of 320 symbols per constellation. The pdf of V.29 is shown as a grayscale image with intensities representing the chance of having one constellation vertex within the corresponding resolution cell. Note that high points are centered around the original 16 vertices, Fig. 3. All results are reported for Eb/No~7 dB and peak phase lock error of \(\pi/8\).

![Image of V.29 constellation pdf]

**Figure 3.** The pdf of the random field model of a reconstructed V.29 constellation. Grayscale intensity is proportional to the likelihood of having one vertex in the corresponding resolution element.

We can now evaluate (8), using a 16QAM model, in response to an unknown modulation type, high noise and non synchronous receiver. V29 is used as the test case. One such reconstruction superimposed on the pdf of the 16QAM constellation is shown in Fig. 4. The decision function evaluated for this case resulted in numbers of extremely large magnitude due to the fact that many of the solid circles in Fig. 4 fall in regions where the pdf of the model is close to zero. The opposite result is obtained by evaluating (8) for an unknown modulation type of 16QAM. The magnitude of the decision function for this case is finite and very stable. Over 25 different realizations of a V29 resulted in a decision functions with a standard deviation of just 0.9 with a mean of 11.5. This is a
virtually a perfect recognition rate despite the close similarity of the two constellations.

**Figure 4.** A single received V.29 fails to match the 16QAM model. White circles indicate the unknown constellation.

**Figure 5.** A received 16QAM modulation is a much closer fit to the 16QAM model even under high noise and large phase lock error.

6. CONCLUSIONS

We have demonstrated that constellation shape is a robust signature for modulation recognition. This algorithm is applicable to any digital modulation type as long as its constellation can be uniquely described. Demonstrated performance levels exceed existing benchmarks even in a non-coherent environment seldom addressed elsewhere. Additional work is being done to model the effect of fading channels on constellation shape matching.

ACKNOWLEDGMENTS

The author gratefully acknowledges the support of Office of Naval Research under grant N00014-94-1-1052.

7. REFERENCES


[8] Constelation shape matching slides online at http://www.ece.vill.edu/~mobasser/icassp98


